CAN GOOGLE MAPS POPULAR TIMES BE AN ALTERNATIVE SOURCE OF INFORMATION TO ESTIMATE TRAFFIC-RELATED IMPACTS?

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Word count: 4,474 words text + 10 tables/figures x 250 words (each) = 6,974 words

1st August 2017
Submitted for consideration for publication and presentation at the 97th Annual Meeting of the Transportation Research Board, January 7-11, 2018.

ABSTRACT

In almost every transport policy document the mitigation of road transport externalities such as traffic congestion, emissions or noise is one of the main targets. The deployment of ICT (Information and Communication Technologies) tools in transportation systems has played a critical role in increasing the sustainability in urban areas. In recent years, many initiatives tried to estimate traffic variables using alternative sources of information or explore potential correlations between traffic-impacts and data from social media as traditional data collection is usually considered costly and lengthy. The aim of this paper is to explore the potential of using Google Maps feature "Popular times" as an alternative source of information to predict traffic-related impacts. For that purpose, its relationships with traffic volumes, travel times, pollutant emissions and noise of different areas in different periods were examined using linear regression models. Different data sets were collected: i) crowdsourcing information from Google Maps; ii) traffic dynamics with the use of a light-duty vehicle equipped with a GNSS data logger; and iii) traffic volumes. The emissions estimation was based on the concept of Vehicle Specific Power (VSP), while noise estimations were conducted with the use of "The Common Noise Assessment Methods in Europe" (CNOSSOS-EU) model. The findings of this study showed encouraging results as it was possible to establish clear relationships between popular times and traffic volumes, CO_2 emissions and noise levels proving the potential of using web-based information as a cost efficient and effective data to estimate traffic-related impacts.

Keywords: ICT, Google Maps, Crowdsourcing, Emissions, Noise, Transportation Externalities

1. INTRODUCTION AND OBJECTIVES

Road transportation is responsible for many external effects, such as air pollution, accidents, traffic congestion and noise (*1*). The reduction of the aforementioned negative externalities are almost the main target objectives in every transport policy document in order to promote sustainable and environmental-friendly mobility (*2*). The global financial crisis that started almost a decade ago has also affected the transportation sector. In recent years, funding for services and infrastructure has been reduced significantly resulted in the decline of the reliability and effectiveness of transportation systems. Under the current circumstances the collection of high quality data to support their operation has become more complicated taking also into consideration that traditional methods are usually costly, lengthy, limited to specific areas (*3*) and the data have poor quality (*4*). However, the possibilities that arise from the recent advancements in communications technologies can provide alternative sources of information that will overcome the current barriers offering real-time data that captures the patterns, needs and experiences of road users. Social media and web services can considered both as a cost efficient and effective data input having valuable information to be harvested, although their use in transport planning and management is still sporadic (*5*). This type of information has the capacity to complement or even replace in certain cases traditional data after distinguishing the useful from the useless data and examining its utility and reliability.

In the last years, many studies have shown attention to explore the potential of using web-based data sources for transport planning, management or operation (*6*). The real-time information that they provide allow commuters to improve their travel experience and transportation authorities to enhance their services quality. More specifically, it can allow city and transport planners to gain a better understanding of mobility patterns and needs, while for individuals to move freely and reducing travel time (*7*). Human mobility is possible to be explained by 10% to 30% of social relationships and 50% to 70% by periodic behaviour (*8*).

Many initiatives also tried to estimate traffic-related impacts using alternative sources of information (*3*). Tostes et al. tried to estimate traffic jams using information that acquired from Bing Maps in the city of Chicago (*9*), while Ni et al. developed a short-term traffic flow prediction model based on Twitter features and focused on traffic conditions prior to sport events (*10*). Social media data has also been examined as a new data source to estimate travel demand. Location-based social networking (LBSN) data was used to estimate origin-destination (OD) matrix as compared to traditional methods can provide much higher temporal resolution at a lower cost (*11*; *12*). In another study, Lee et al. in 2013, an OD matrix based on social-media travel data acquired from Twitter was compared with the results of a traditional travel demand model in the Greater Los Angeles metropolitan area and the preliminary findings were especially encouraging (*13*). Under the same context, Chaniotakis et al. examined data from different social media and compared it with conventional travel-diary surveys from the city of Thessaloniki, Greece, aimed at identifying alternative sources of information to improve Intelligent Transportation Systems applications (*14*).

A growing body of research also explores potential correlations between traffic-impacts and data from social media. For instance, Ribeiro et al. found a mentionable correlation between real traffic conditions and data from Twitter regarding traffic conditions in Belo Horizonte, Brazil (*15*), while Tian et al. validated traffic incidents mentioned by social media users by comparing them with field cameras data in Austin, Texas (*16*). Pereira et al. developed a probabilistic data analysis model aimed to specify habitual and non-habitual overcrowding hotspots in public transportation systems using also data from social networks. The results showed the potential applicability of the proposed model in different cases (*17*). Finally, Teixeira et al. explored the correlations between traffic congestion, emissions, speeds and traffic volumes with Google Maps traffic data with preliminary findings showing encouraging results in urban arterials (*18*).

Popular times is a new feature in Google Maps that was launched in July 2015 and allows users to have a better insight on a place's busy time periods. With that information people are assisted in their decision-making process regarding the best time to visit a specific place or area. The information that is usually included is (Figure 1):

- Graph per day and hour showing how busy is a specific location based on historical data;
- Live activity data of how busy is the area updated by real-time information and easily comparable with the average values;
- Visit duration, showing the average time people spend at the specific place.

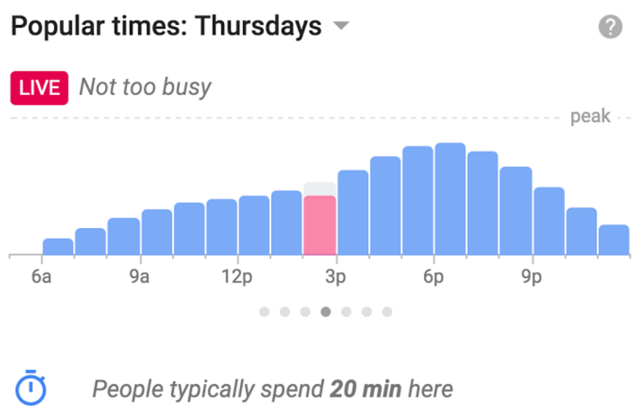

FIGURE 1 Example of Google Maps "Popular times".

The aim of this paper is to explore an alternative source of information to predict traffic-related impacts. For that purpose, a previous study (*3)* was expanded by including a new study area with different characteristics but also conducting new data collection in the previous studies areas in order to provide seasonal comparisons. In addition to the previous research, also noise analysis is included. This study aims to examine in depth the potential of using Popular times of Google Maps as a reliable and low-cost data to estimate traffic volumes, travel time, pollutant emissions and noise.

2. METHODOLOGY

2.1. Case Studies

In this study, three important commercial zones in areas with different characteristics are examined (Figure 2). Two of them are in the city of Aveiro in Portugal, while the last one is in Badajoz, Spain. The first study area is Aveiro Shopping Center, which is located in the industrial zone of the city. Four road links consist the case study. Link l1 is the main entrance to the commercial zone, while l2 is the main exit of it. Links l3 and l4 connect the city of Aveiro with the industrial zone. The studied links are located between roundabouts and there are various unsignalized intersections with minor roads from both sides. One crosswalk interrupts both links l1 and l2. The second study area is Glicínias Plaza Shopping Center, which is within the urban area of the city. The main links that lead to (link l5) and out (link l6) of the shopping center are examined. The links are between roundabouts, one crosswalk interrupts the links and in link l6 there is the only entrance and exit to a gas station. The last studied area is a Hypermarket in Badajoz. Links 7 and 8 consist the main entrance and exit to the shopping center. The land use of the area is mainly residential, the links are between roundabouts, while three crosswalks interrupt them.

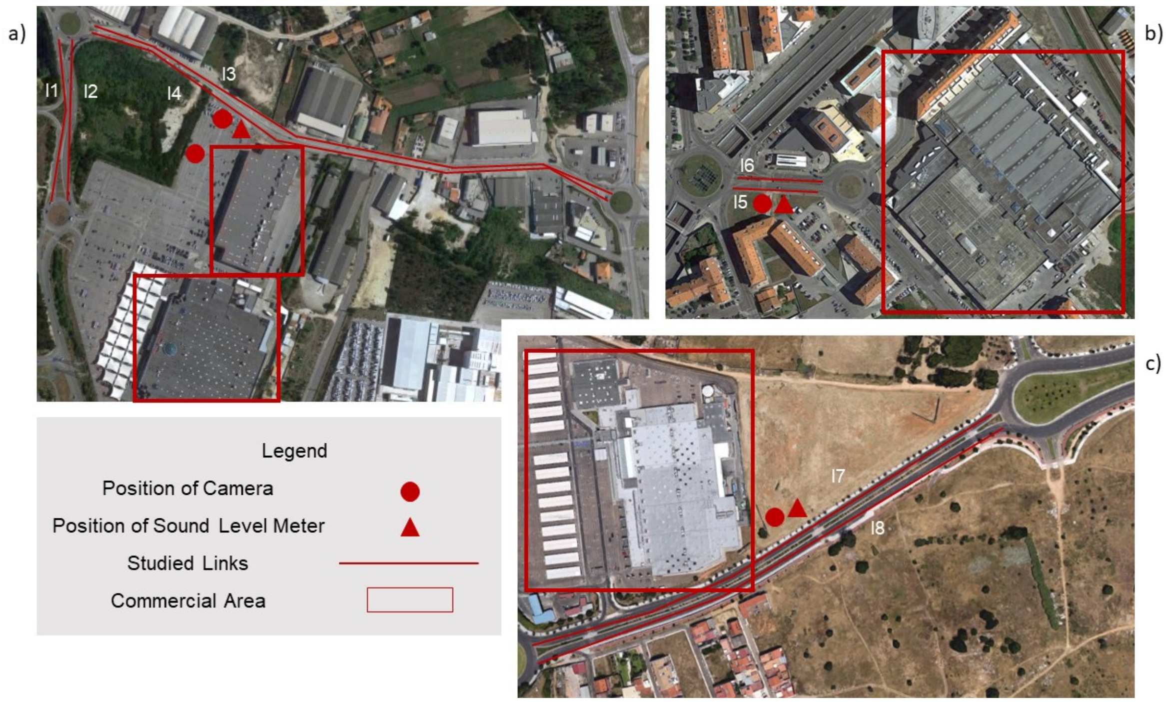

FIGURE 2 Studied areas a) Aveiro Shopping Center; b) Glicínias Plaza Shopping Center; c) Hypermarket (Badajoz).

2.2. Data Collection

Data collection was conducted during weekdays and weekends in different seasons of the year (Winter – Summer) in order to achieve a diversified range of traffic demand and conditions. For the purpose of the analysis three different data sets were collected:

- Crowdsourcing information in real time regarding the popularity of the studied commercial areas from Google Maps;
- Traffic dynamics (travel time, speed, and acceleration) with the use of a light-duty vehicle equipped with a GNSS data logger that performed 10 runs per hour for each link,). To increase the heterogeneity of the driving behaviour different drivers were used (*19*), while the probe vehicle was moving according to their perception of traffic flow (*20*);
- Traffic volumes with the use of cameras in 15 minutes interval;
- Number of vehicles in the parking lot and vehicles occupancy in Aveiro Shopping Center.

2.3. Methodological Approach

To investigate the potential of using Google Maps feature "Popular times" as an alternative source of information to predict traffic-related impacts, this study focused on exploring its relationships with traffic volumes, travel times, emissions and noise of different areas in different periods.

Google Maps present popular times with the use of a bar chart without providing values. For the purpose of this paper, we assume that the minimum value of the bar is zero and the maximum is one and we divided it in ten equal parts giving them the respective values.

Furthermore, to examine its reliability, correlations between the parking occupancy of a specific commercial area and the popularity of that location during that period were explored. The relationships between the predictors and the response were examined using linear and polynomial regression models. Specifically, we focused on linear and quadratic models to describe data, since they are relatively simple and easily interpretable, and application of higher order polynomials (or even more complex models) may result in overfitting (*21*).

Two methodological approaches were followed to find the aforementioned relationships based on a standard interval of 15 minutes. In the first approach, values of each studied variable were compared to popular times' value in the end of the respective interval, while in the second the comparison was made with the value in the end of the next 15 minutes period. The results only of the first approach are presented as the correlations were higher.

2.4. Emission Estimation

For the estimation of the emissions, the concept of vehicle specific power (VSP) was used as it allows the estimation of instantaneous emissions from second-by-second vehicle dynamics, accounts for the effect of different driving modes (acceleration, deceleration, cruise, idling), and also includes a wide range of engine displacement values (<2.5 L) and can be applied to the Portuguese and Spanish car fleet (*22*).

VSP is a function of acceleration and deceleration, instantaneous speed and slope that can be expressed as:

$$VSP = v[1.1a + 9.81(a\tan(\sin(grade))) + 0.123] + 0.000302v^3 \quad (1)$$

where: v = vehicle speed (m/s), a = vehicle acceleration/deceleration rate (m/s^2), grade = vehicle vertical rise divided by the horizontal run (%).

VSP bins are categorized into 14 modes and each mode is defined by a range of values associated to an emission rate (*23*). This study is focused on the estimation of CO_2 and NOx emissions (respectively, a greenhouse gas and a critical local pollutant - precursor to troposphere ozone and with demonstrated effects in human health).

For the purpose of this study the following distribution fleet composition was considered:

- 38% of light duty gasoline vehicles and 62% of light duty diesel vehicles for the Portuguese studied areas;
- and 44% of light duty gasoline vehicles and 56% of light duty diesel vehicles for the Spanish studied areas based on the respective national vehicle classification (*24*).

Although some differences may occur in total absolute emissions estimation, the authors assume this approach as suitable to reflect the relative emissions variation associated to different driving behavior in the studied road links.

2.5. Noise Estimation

For the noise estimation, "The Common Noise Assessment Methods in Europe" (CNOSSOS-EU) model is used as a uniform approach to noise assessment in European countries. It is based on the assessment of the noise produced by a single vehicle, summing the rolling and the propulsion noise per each frequency octave (in the range 125 Hz - 4000 Hz). The former noise has a log dependence by the mean speed of the traffic flow, while the latter has a linear dependence. Once the power of the source "vehicle" is evaluated for each category of vehicles (passenger cars, medium heavy vehicles, heavy duty vehicles), the presence of a given number of vehicles per hour and the propagation model are implemented. A line source is assumed and the formula can include favorable and homogeneous conditions. Several attenuation factors, such as reflections, diffractions, atmospheric effects, ground absorption, etc., can be included in the formula, in order to better simulate the phenomena that affect the propagation (*25*). The noise emission of a traffic flow per each link was based on the average speed recorded with the GPS data logger while the vehicle flow was estimated based on the videotaping. Finally, with the use of Equation (2), noise levels were estimated for each street.

$$L_{eq} = 10\sum 10^{Li/10} + 10^{Lj/10} \tag{2}$$

where: Leq = integration of the estimated sound level of directions Li and Lj (*25*).

3. RESULTS AND DISCUSSION

3.1. Reliability of Popular times

As a first step of the analysis the reliability of Popular times is examined in the case study of Aveiro Shopping Center. As already mentioned, the commercial area is located in the industrial zone of the city and the low frequency level of public transport services encourage the use of private vehicles. To test the reliability of Popular times as a predictor variable for monitoring the area's popularity, the number of vehicles in the parking lot was monitored in 15 minutes intervals during the study period. The analysis (Figure 3) showed that there is a high correlation between the parking occupancy (R^2= 0.89), encouraging the use of the variable to estimate the number of visitors to a certain place. The vehicle occupancy rate has been also recorded (1.81 persons per vehicle) which allowed to estimate that an increase of 0.1 in Popular times value represents an increase in demand of 142 vehicles and 248 visitors. Understandably, this response would change in other case studies according to the overall attractiveness of each commercial area.

a) b)

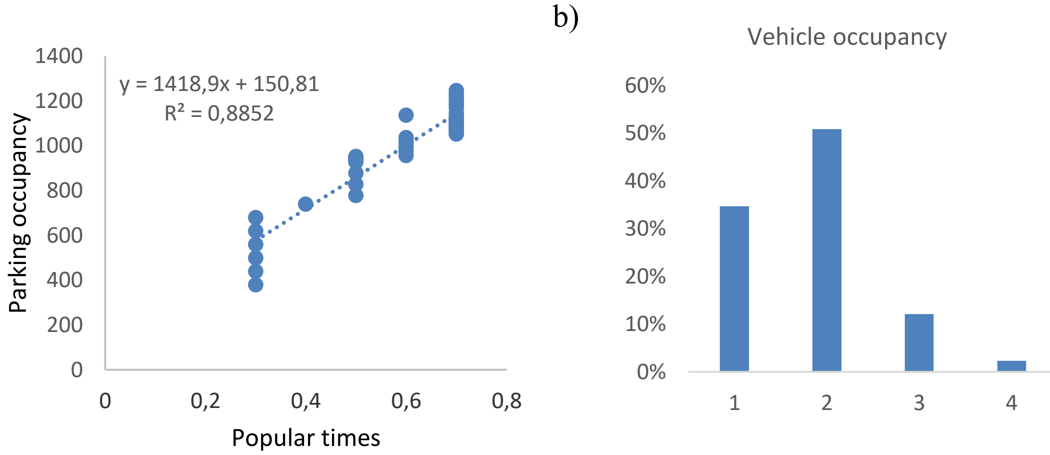

FIGURE 3 a) Linear regression between Popular times and parking lot occupancy; b) Relative distribution of vehicle occupancy.

Most of the examined correlations presented good results (Figure 4) with statistically significant values (p-value<0,05), which means that the chosen models significantly predict the response variable. In general, higher coefficient of determination values were obtained for traffic volumes, CO_2 and noise estimations, meaning Popular times can explain them better. Regarding, NOx emissions results were weaker as are strongly affected by drivers' behavior. Low results were acquired for links l3 and l4 during the weekend mainly because there were not significant traffic flows from those links to the shopping area.

Links	Study Period	Variables	Coefficients of the Model		R^2	p-value	Links	Study Period	Variables	Coefficients of the Model		R^2	p-value
			a	b	(Coefficient of determination)					a	b	(Coefficient of determination)	
l1	weekday	Traffic volumes	154.11	35.161	0.88	2.19E-09	l1	weekend	Traffic volumes	222.55	-9.915	0.86	1.04E-09
		System CO_2	8450.9	256.63	0.93	4.02E-10			System CO_2	9271.9	21.937	0.77	6.71E-09
		System NOx	29.76	-3.271	0.76	6.88E-07			System NOx	22.67	6.1765	0.72	1.95E-06
l2	weekday	Traffic volumes	186.39	15.599	0.85	1.87E-04	l2	weekend	Traffic volumes	166.16	21.963	0.89	2.44E-11
		System CO_2	7517.6	168.12	0.82	1.81E-05			System CO_2	5402.8	1479.8	0.78	1.17E-09
		System NOx	28.076	-2.743	0.67	6.49E-04			System NOx	14.025	6.2858	0.31	6.34E-07
l1-l2		Noise	4.982	54.503	0.85	3.20E-06	l1-l2		Noise	7.1113	57.653	0.75	6.08E-08
l3	weekday	Traffic volumes	111.51	66.77	0.7	4.20E-07	l3	weekend	Traffic volumes	26.175	81.263	0.09	7.91E-08
		System CO_2	14786	6997.8	0.55	1.54E-06			System CO_2	2480.2	10958	0.06	4.98E-08
		System NOx	37.326	16.379	0.59	1.09E-06			System NOx	2.4859	30.514	0.01	9.84E-08
l4	weekday	Traffic volumes	82.264	98.755	0.53	1.84E-06	l4	weekend	Traffic volumes	14.398	92.259	0.01	9.22E-06
		System CO_2	12396	10989	0.53	1.61E-26			System CO_2	-1816	14053	0.01	3.89E-05
		System NOx	36.757	24.407	0.55	1.36E-06			System NOx	-10.07	39.676	0.02	5.26E-05
l3-l4		Noise	9.9992	54.917	0.55	9.38E-06	l3-l4		Noise	-2.539	61.884	0.14	1.86E-07
l5	weekday	Traffic volumes	323.33	-18.5	0.55	7.90E-15	l7	weekday	Traffic volumes	253.44	33.219	0.5	1.35E-09
		System CO_2	6566.9	-249	0.48	5.20E-14			System CO_2	45123	1314.9	0.62	4.92E-10
		System NOx	12.661	0.6283	0.44	2.04E-14			System NOx	103.14	5.82	0.56	1.20E-09
l6	weekday	Traffic volumes	401.89	-58.21	0.81	3.65E-14	l8	weekday	Traffic volumes	235.97	56.292	0.48	3.42E-11
		System CO_2	23681	-6430	0.52	2.29E-08			System CO_2	37136	8180.8	0.46	5.52E-11
		System NOx	47.497	-11.53	0.47	1.98E-08			System NOx	83.132	31.149	0.3	6.74E-10
l5-l6		Noise	7.8001	54.922	0.69	8.10E-14	l7-l8		Noise	5.9122	60.244	0.39	1.02E-09

FIGURE 4 Model Variables between Response Variables and Popular Times.

3.2. Traffic Analysis

The analysis regarding the correlations between Popular times and traffic volumes provided strong results with the better for each link presenting in Figure 5. All models are adequate and statistically significant to fit the data (p-value<0.05). More specifically, in links l1 and l2 there were high correlations between the number of vehicles and the values of Popular times (R^2 > 0.85) both during the weekday and the weekend as the two links consist the main street that leads to the shopping area. On the other hand, the lowest results were achieved in links l7 and l8 mainly because many drivers used the secondary entrance of the hypermarket zone.

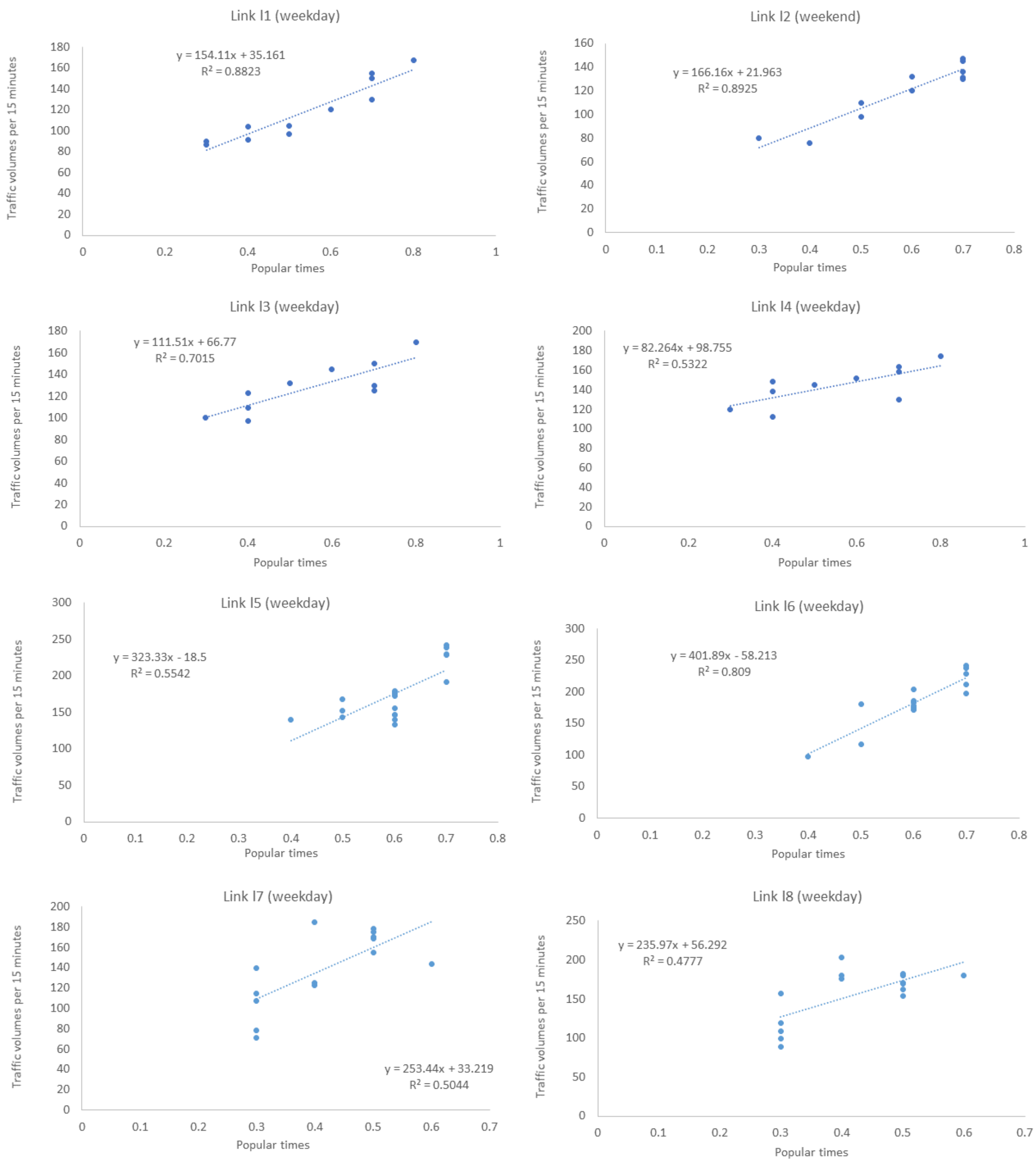

FIGURE 5 Linear regressions between traffic volumes and Popular times.

3.3. Emission Analysis

Figures 6 to 8 present the linear regressions between Popular times and CO_2 and NOx emissions. Links l1 and l2 presented the strongest correlations regarding emissions, both for CO_2 and NOx compared to the remaining links. Popular times can explain 94% and 76% of CO_2 and NOx variability, respectively, in l1, and 82% and 67%, respectively, in l2. Regarding l3 and l4, weaker relationships were observed, however, Popular times feature is still able to explain around 59% of their variability in l3, and 53% and 55% of CO_2 and NOx variability in l4. For links l5 and l6, 48% and 52% of CO_2 emissions and 44% and 47% of NOx emissions can be explained. Regarding the results in the studied area in Badajoz, Popular times can explain 62% and 56% of CO_2 and NOx variability in l7, while in l8, respectively 46% and 30% of CO_2 and NOx variability.

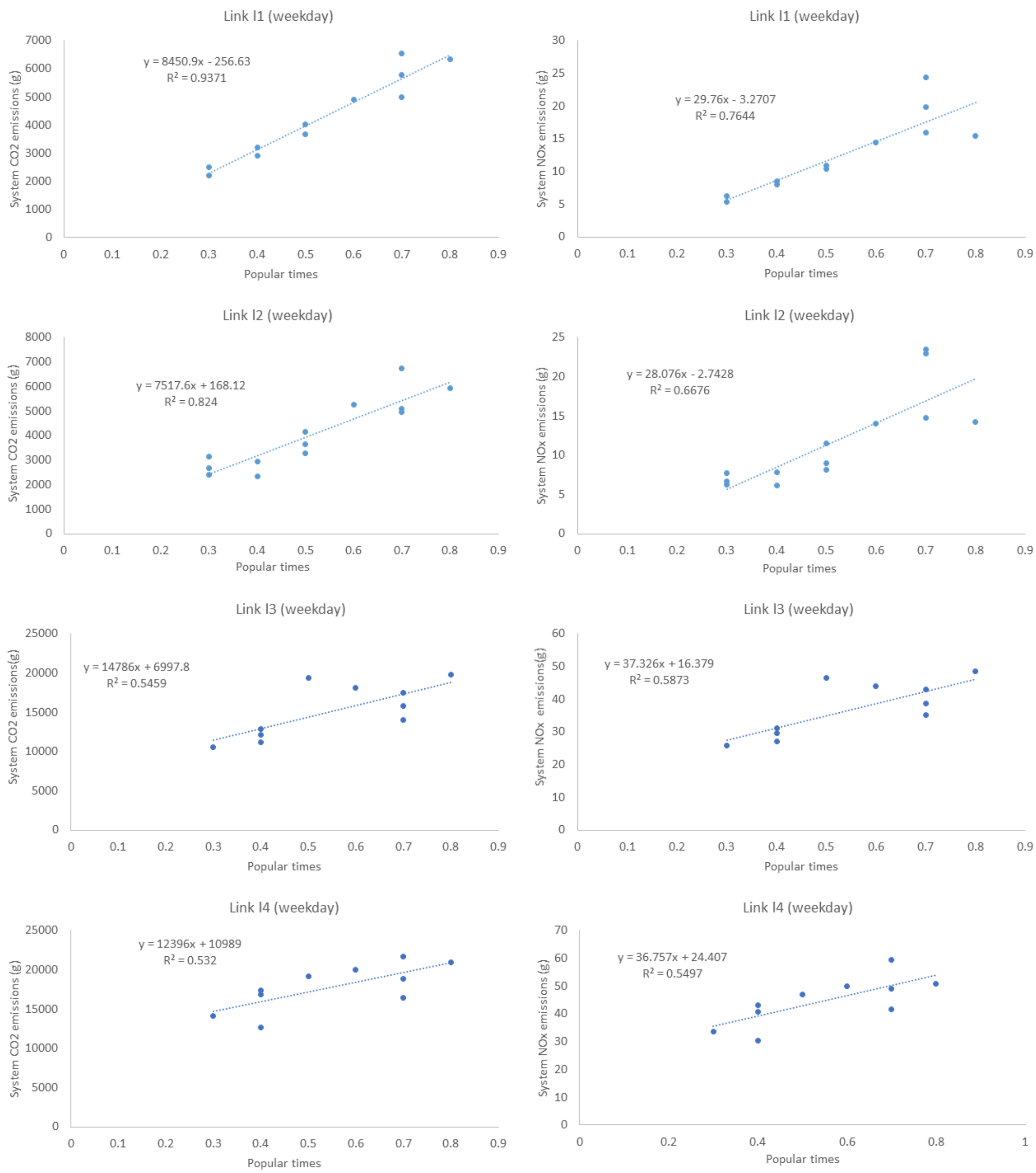

FIGURE 6 Linear regressions between CO_2 and NOx emissions and Popular times for Aveiro Shopping Center.

Results on correlations with NOx emissions are rather weaker, when compared with CO_2, since such emissions are strongly affected by drivers' behavior and road links were operating at free flow during most of the studied period, leading to a higher variability on drivers' perceptions of the roadway conditions. These results reinforce that Popular times can be used for estimating emissions or at least for minimizing the error in its estimation.

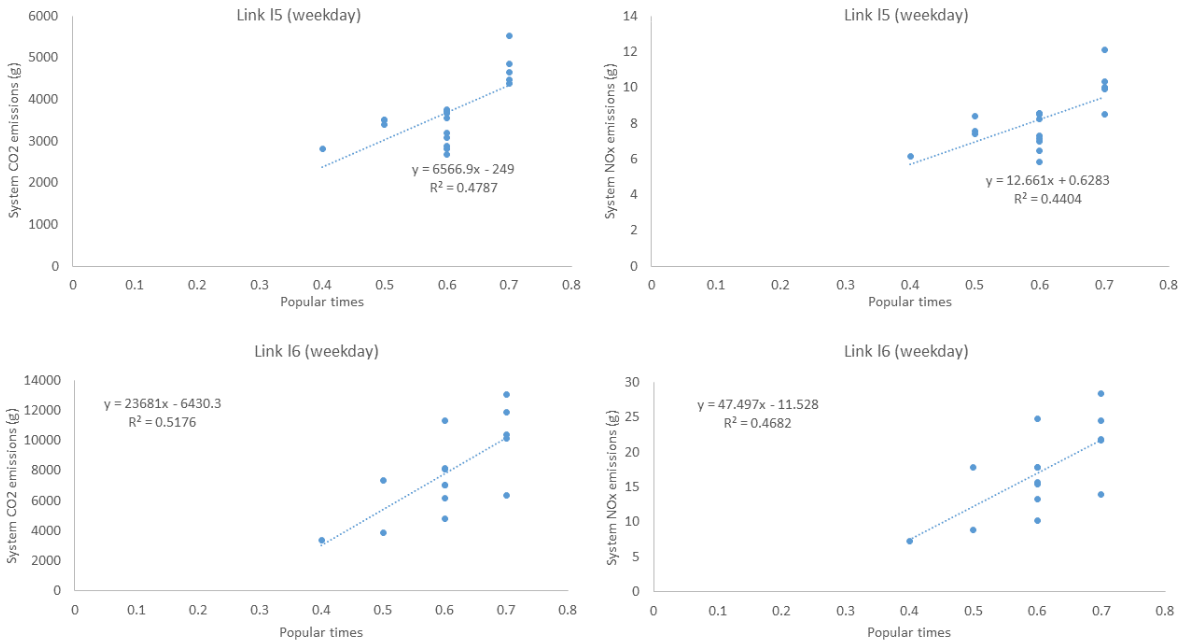

FIGURE 7 Linear regressions between CO_2 and NOx emissions and Popular times for Glicínias Plaza Shopping Center.

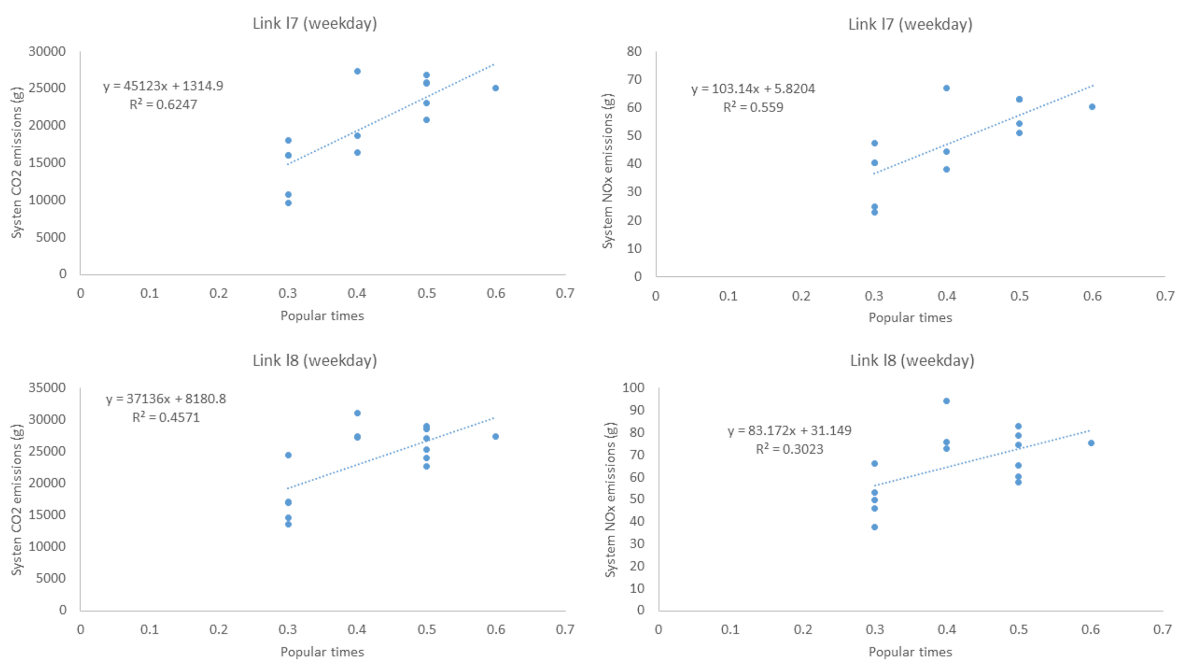

FIGURE 8 Linear regressions between CO_2 and NOx emissions and Popular times for Hypermarket (Badajoz).

3.4. Noise Analysis

The relationships between noise and popular times were also examined by combining the line noise sources from both directions of each street (Figure 9). As in the previous analyzes, the linear regression models are only valid for the range of popular times values that were examined. However, for these intervals the popular hours can reasonably explain the variability in the noise levels in the studied links. In links 1 and 2, popular times can explain on weekends and on weekdays 85% and 75% of road noise levels variability, respectively. Due to the higher demand on weekends (also to other commercial areas) an increase of 0.49 dBA was observed on weekdays and 0.71 dBA on weekends for a decimal increase in Popular times values. In Link 5 and L6 popular times explains 68% of noise variability. In Links L7 and L8 popular times can justify only 38% of noise emissions. This lower value is related both to lower relation with volumes and to a higher diversion of average speed.

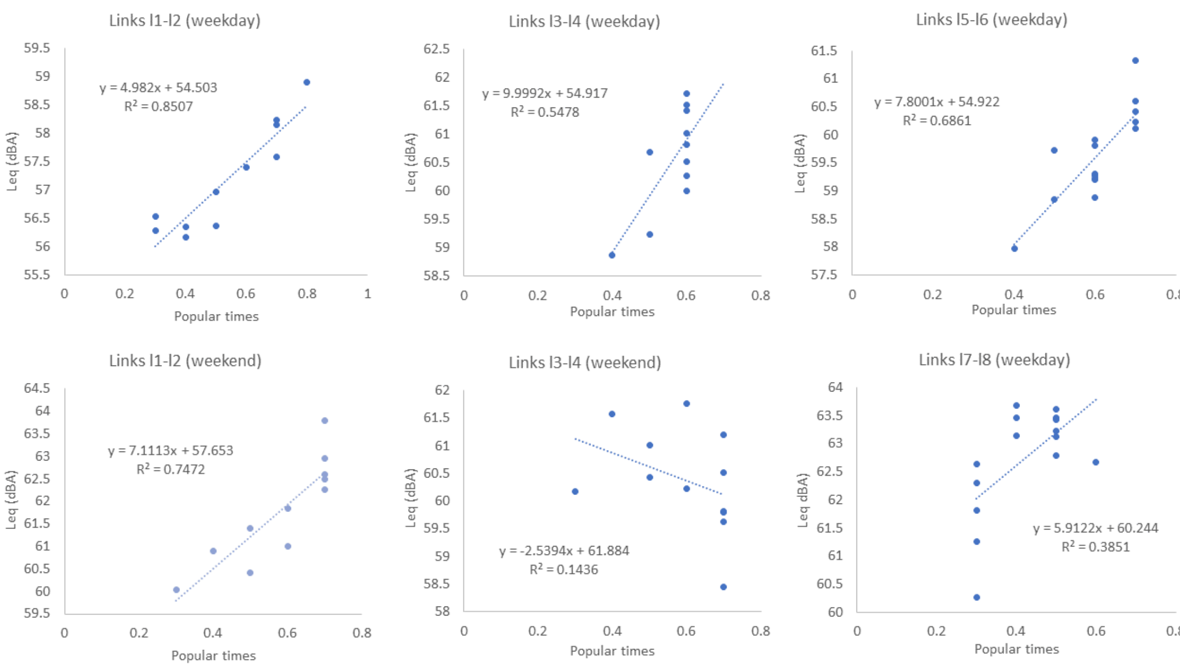

FIGURE 9 Linear regressions between noise estimation and Popular times.

3.5. Comparative Analysis

In this section, a comparative analysis was conducted based on data collection during different periods of the year. More specifically for links l1 to l6, repetitive data collections were made during winter and summer (Figure 10). The analysis showed that the models are mainly dependent on the day or the season. In links l1 and l2, because they consist the main street connection to Aveiro shopping center, the variability is less. Regarding links l3 and l4, it is possible to suggest that during the summer months the lack of any kind of correlations is because the street serves as a connective link to the city of Aveiro. The results regarding links l5 and l6 are may explained of the fact that both the links are used for different trip destinations.

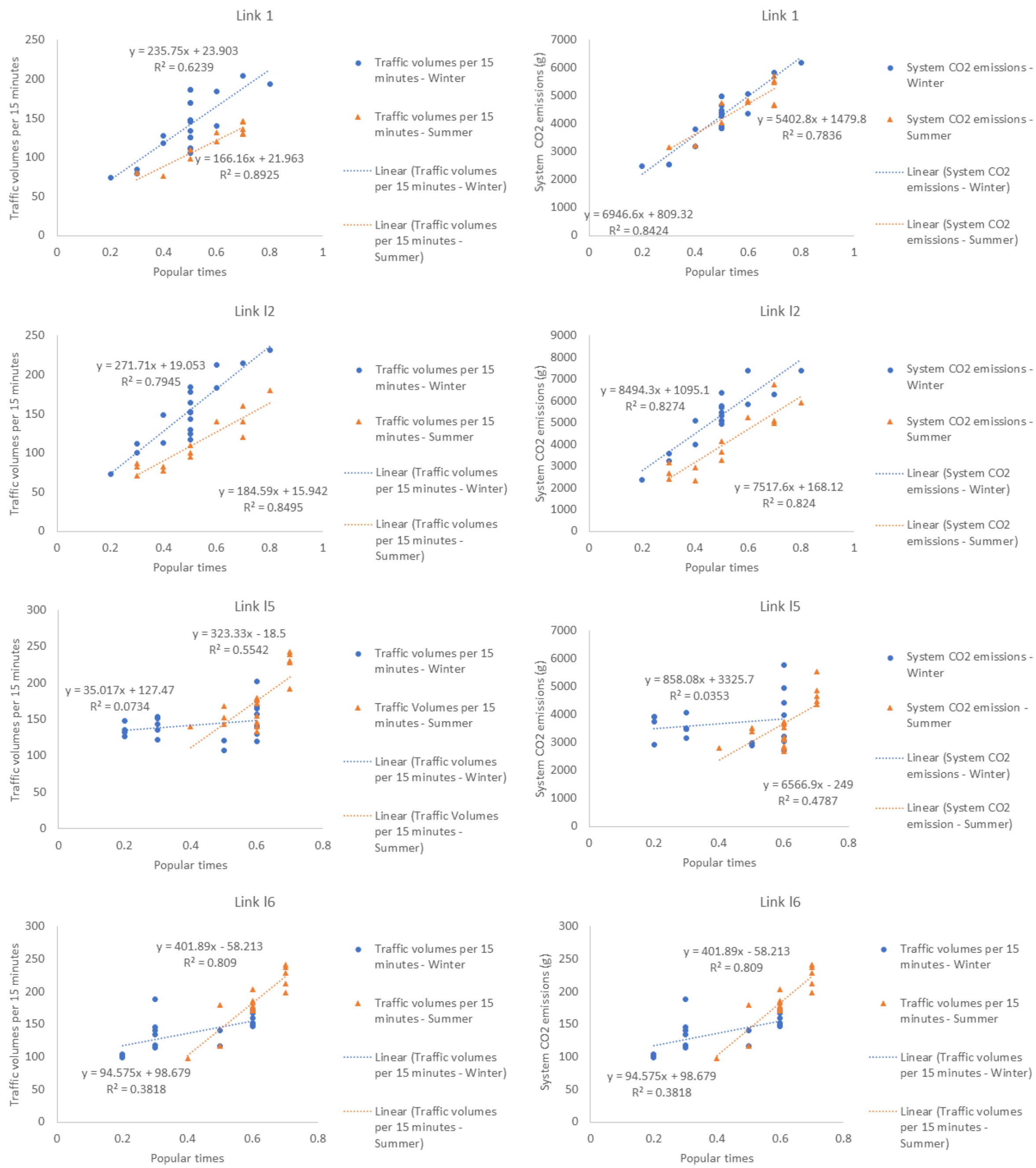

FIGURE 10 Seasonal comparison of studied areas.

4. CONCLUSIONS

This study assessed the potential of using Google Maps Popular times to predict traffic volumes and traffic externalities. Three different study areas and 8 links near to important shopping areas in Portugal and Spain have been assessed during weekdays and weekends in different seasons. Simple linear regression models were applied to fit empirical observations and simulated road traffic, NOx and CO_2 emissions, and noise levels with Popular times. The analysis of the results suggested that for specific time periods it is possible to establish clear relationships between popular times and traffic volumes (up to 90%), CO_2 emissions (up to 98%) and noise levels (up to

85%). Popular times have shown to have lower capibalitty to explain NOx emissions due to higher variability in driving behavior and higher dependence of individual acceleration and deceleration patterns under free flow regime. However, in shorter links such as l1, Popular times can justify 76% of NOx emissions variability.

Regarding the main question of the paper "can Popular times be used as an alternative source of information to predict traffic related impacs?" the answer is affirmative but under a considerable set of restrictions. While in some links, it has been shown that the models can be applied in different seasons of the year, in others the parameters of the regressions depend on the season or the day. This fact suggests that the relative scale of the Google Maps Popular times is not a uniform approach for different periods of the year and there is a considerable seasonal variability in the OD matrix of road users of the assessed road links. Before the implementation of a monitoring system based on this type of information, it will be necessary to collect data over an extended period or to have access to similar data sets, e.g. based on absolute values for urban zones on open data platforms. This type of information would be especially useful in cities where there is limited funding to monitoring traffic conditions through traditional traffic monitoring systems and environmental sensors. Furthermore, leisure trips are harder to predict and this information can contribute to adjust spatio-temporal information of urban OD matrices with higher accuracy.

This type of information and crowdsourcing informations may be considered an asset to anticipate in advance potential congestion solutions due to high levels of popularity. Moreover, it may allow to contribute to the optimization of intelligent transport systems such as partial-metering strategy or dynamic traffic lights. Finally, the collected environmental information can be included in environmental information systems and real-time link-based information can be deployed in eco-routing platforms.

Future work will contain the development of a global model that could be used to estimate traffic volumes, CO2 and NOx emissions, and noise in links near commercial areas using Popular times as predictive variable. In addition, integrated analysis is going to be conducted based on street networks and not on seperated links.

ACKNOWLEDGMENTS

The authors acknowledge the support of Toyota Caetano Portugal (that allowed the use of the vehicles), Project CISMOB (PGI01611 funded by Interreg Europe Programme), Strategic Project UID-EMS-00481-2013 (FCT – Portuguese Science and Technology Foundation), CENTRO-01-0145-FEDER-022083, @CRUiSE project (PTDC/EMS-TRA/0383/2014, funded within the Project 9471 – Reforçar a Investigação, o Desenvolvimento Tecnológico e a Inovação (Project 9471 – RIDTI) and supported by the European Community Fund FEDER) and MobiWise project (P2020 SAICTPAC/0011/2015) (co-funded by COMPETE2020, Portugal2020 - Operational Program for Competitiveness and Internationalization (POCI), European Union's ERDF (European Regional Development Fund), and FCT). J. Bandeira also acknowledges the support of FCT for the Scholarship SFRH/BPD/100703/2014.

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